Ensemble methods and online learning for creation and update of prognostic scores in HF patients

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Summary

- How to create a parsimonious event risk score with ensemble methods?

- How to update an ensemble score in the case of a data stream?
  - Tools for generalized linear regression: stochastic approximation processes.

Parsimonious scores by an ensemble method
Context

- Scores are mainly built using “classic” statistical methods : logistic regression, Cox regression…

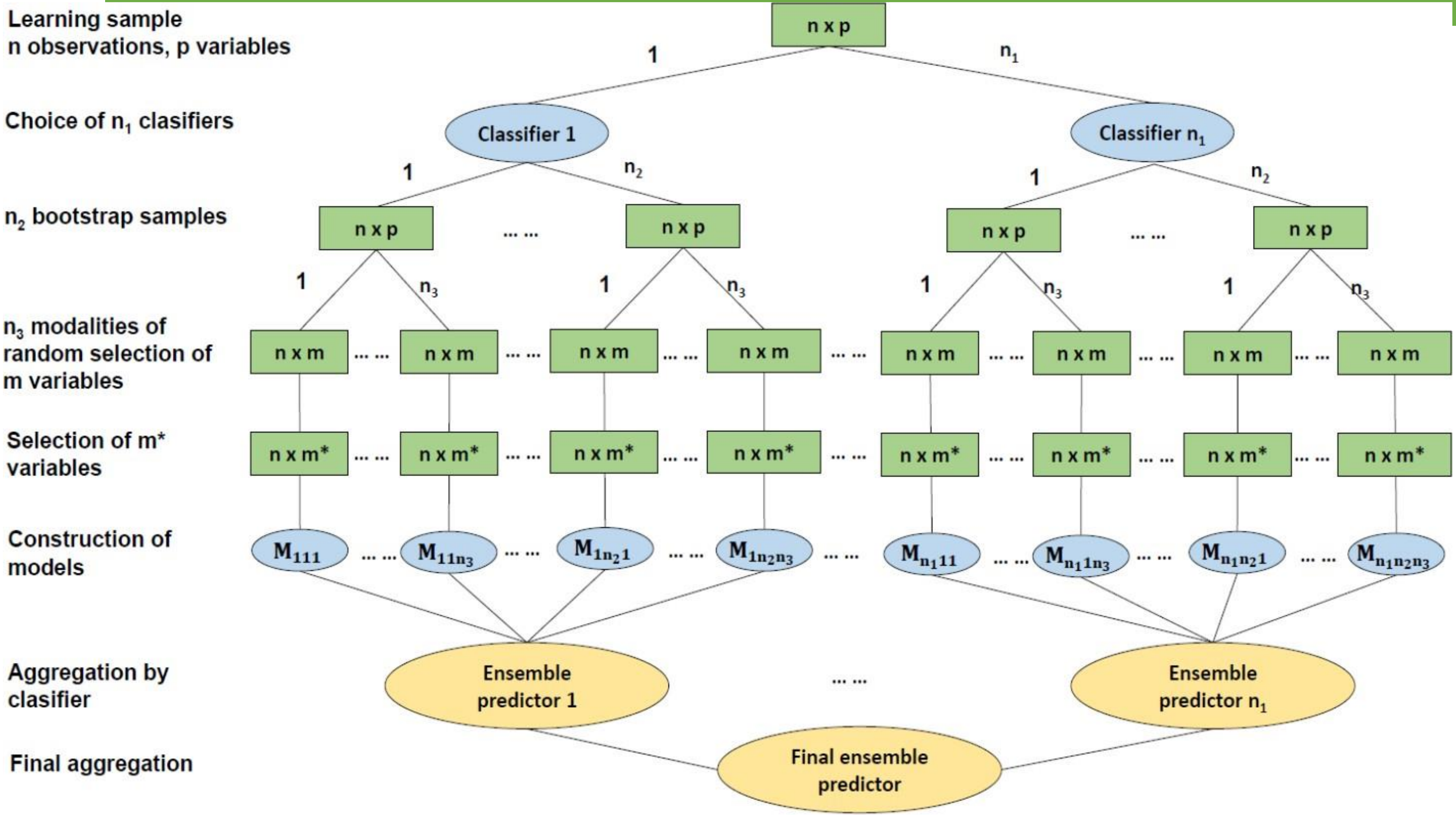
- Another possibility: use ensemble methods.

- Ensemble method: collection of predictors (with different learning rules, samples, selection of variables, etc.) whose predictions are then aggregated.

- Often obtain better results than individual predictors.

Parsimonious scores by an ensemble method

Batch method – Duarte *et al.* 2018



Duarte K, Monnez JM, Albuisson E. Methodology for Constructing a Short Term Event Risk Score in Heart Failure Patients. *Appl Math*. 2018.

Parsimonious scores by an ensemble method

Context (2)

- Common difficulty in the construction of prognostic scores: choose the variables to include.
- Balance between better statistical fit and practical application.
- As we want to use an ensemble method, usual selection methods are not easily applicable.

→ Methodology for constructing parsimonious event scores combining a stepwise preselection of variables and the use of ensemble scores

Parsimonious scores by an ensemble method
Selection methods

- We proposed several methods and compared them.

- Backward methods (need a score formula):
  - Build an ensemble score with a large number of variables
  - Backward selection of the variables, based on the coefficients in the score

- Forward methods (do not need a score formula):
  - Forward selection of the variables which maximize AUC

- A preselection of variables by classifier can precede the methods

Parsimonious scores by an ensemble method

Illustration for short-term predictions in chronic HF patients

- Data: subsample of the GISSI-HF trial
- Data management: couples patient-visit; winsorized and transformed variables; balancing of the sample (duplication of the cases)
- Event: hospitalization for aggravating HF or death from HF within 180 days of a visit

- 3 methods compared: similar selections of variables and performances

- 4 parsimonious scores using the fastest method:

Score's name	S3.26	S3.15	S3.8	S3.2
Nb of variables used	26	15	8	2
AUC OOB final score	0.8137	0.8002	0.7835	0.7523

Online logistic regression
Online learning & online standardization

Online learning:

- Analysis of a data stream or of big data.
- Update the results in successive steps, taking into account new data at each step.
- A possibility: use recursive stochastic algorithms.

Online standardization of the data:

- Data can be standardized to: avoid a numerical explosion or apply a shrinkage method (e.g. LASSO).
- Issue for data streams: means and variances are a priori unknown.
- A possibility: do an online standardization.
- Studied for the linear regression: better performance compared to raw data.
- We used a similar approach for the logistic regression.

Online logistic regression
Stochastic gradient processes

Stochastic approximation processes of this form were tested:

$$X_{n+1} = X_n - a_n \frac{1}{m_n} \sum_{j \in I_n} \tilde{Z}_j \left(h\left(\tilde{Z}_j{}' X_n \right) - S_j \right)$$

$$\bar{X}_{n+1} = \frac{1}{n+1} \sum_{i=1}^{n+1} X_i$$

Different variants exist:

- Classical (X_n) or averaged $(\bar{X}_n)$.
- Raw data or online standardized data.
- Different numbers of new observations at each step (m_n).
- Variable step-size or piecewise constant step-size (a_n).

Online logistic regression
Datasets, datastream & comparison

- 24 processes tested on 5 datasets. Data streams simulated by randomly drawing successive data batches from the datasets.

- Usual logistic regression used as gold standard.

- Convergence criterion (norms ratio: $\frac{\|\theta^c - \hat{\theta}_{n+1}\|}{\|\theta^c\|}$) recorded for fixed numbers of observations used and for fixed processing times.

- Processes ranked for each dataset and each recording point. Average rank across all datasets used to compare processes.

Online logistic regression

Comparison for a fixed processing time (60s)

Process	Twonorm	Ringnorm	Quantum	Adult	HOSPHF30D	Mean rank
CR1V	0.055	0.019*	0.288	EXPL	EXPL	-
CR10V	0.061	0.005*	0.310	EXPL	EXPL	-
CR100V	0.073	0.002*	0.333	EXPL	EXPL	-
AR1P50	0.011*	0.019*	0.086	EXPL	EXPL	-
AR10P50	0.002*	0.002*	0.095	EXPL	EXPL	-
AR100P50	0.001*	0.001*	0.102	EXPL	EXPL	-
AR1P100	0.015*	0.029*	0.064	EXPL	EXPL	-
AR10P100	0.002*	0.003*	0.079	EXPL	EXPL	-
AR100P100	0.001*	0.001*	0.090	EXPL	EXPL	-
AR1P200	0.018*	0.052	0.040*	EXPL	EXPL	-
AR10P200	0.002*	0.005*	0.064	EXPL	EXPL	-
AR100P200	0.001*	0.001*	0.076	EXPL	EXPL	-
CS1V	0.139	0.023*	0.173	0.134	0.153	10.0
CS10V	0.182	0.011*	0.057	0.101	0.228	9.0
CS100V	0.227	0.004*	0.071	0.108	0.326	9.0
AS1P50	0.027*	0.025*	0.042*	0.389	0.095	8.6
AS10P50	0.006*	0.005*	0.014*	0.020*	0.053	4.8
AS100P50	0.009*	0.002*	0.007*	0.017*	0.014*	3.2
AS1P100	0.032*	0.037*	0.071	0.386	0.087	9.2
AS10P100	0.005*	0.006*	0.014*	0.025*	0.050*	4.8
AS100P100	0.004*	0.002*	0.007*	0.011*	0.011*	1.8
AS1P200	0.046*	0.060	0.121	0.498	0.112	10.6
AS10P200	0.005*	0.008*	0.017*	0.035*	0.049*	5.4
AS100P200	0.003*	0.002*	0.007*	0.009*	0.012*	1.6

* Denotes a criterion value <0.05

EXPL: numerical explosion

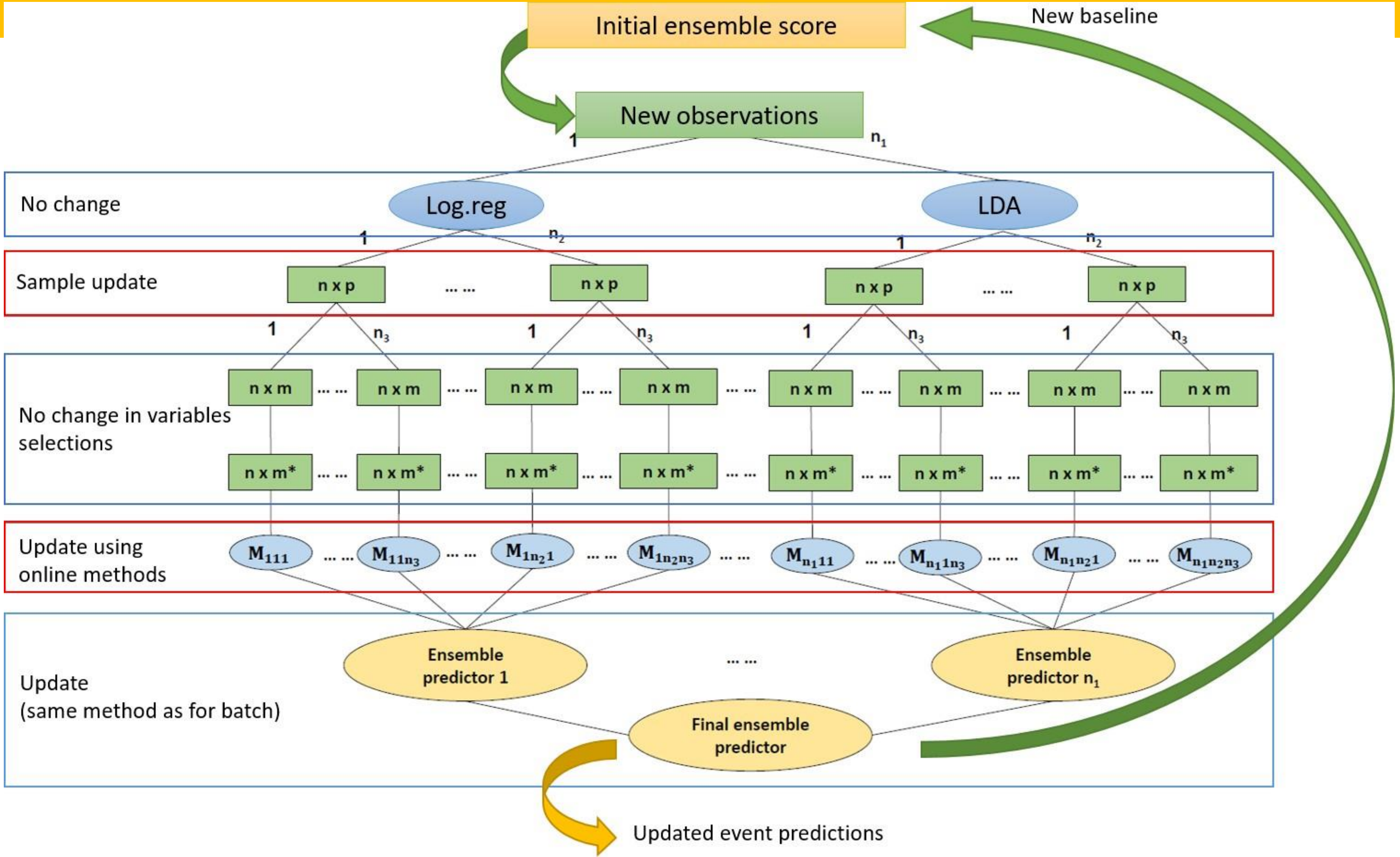
- *Process type:* C for classical SGD, A for ASGD
- *Data type:* R for raw, S for online standardized
- *1st number:* number of new obs. per step
- *Step-size:* V for variable, P for piecewise constant (*2nd number:* levels size)

Online ensemble score
Online method

How to update an ensemble score similar to Duarte et al. in the case of a data stream?

- Choice of classifiers: same as the initial ensemble score.
- Bootstrap samples: use Poisson bootstrap.
- Selection of variables: same as the initial ensemble score.
- Construction of models: use online versions (online linear regression, online logistic regression...).
- Aggregation: same as the initial ensemble score.

Online ensemble score
Online method (2)



Online ensemble score
Experiments

- Same datasets than previously. Data streams simulated by randomly drawing successive data batches from the datasets.

- A batch score was created as reference for each dataset:
  - 100 bootstrap samples.
  - 2 classifiers: logistic regression and linear discriminant analysis (linear regression).
  - 1 modality with all variables.

- 6 online scores using 100N observations and the same parameters.

- Empirical study of convergence toward the reference score ($\frac{\|\theta^c - \widehat{\theta}_{n+1}\|}{\|\theta^c\|}$).

Online ensemble score
Comparison with a fixed number of observations (100N)

Norms ratio between the batch score coefficients and the online scores coefficients:

Process		Twonorm	Ringnorm	Quantum	Adult	HOSPHF30D
CS100V_CS100V	*LDA*	0.0010*	0.0020*	0.0073*	0.0076*	0.0165*
	Log. Reg.	0.0033*	0.0009*	0.0168*	0.1002	0.0566
	Final	**0.0015***	**0.0014***	**0.0083***	**0.0414***	**0.0289***
AS100P50_AS100P50	*LDA*	0.0006*	0.0007*	0.0027*	2.7560	0.0176*
	Log. Reg.	0.0006*	0.0007*	0.0032*	0.0346*	0.0203*
	Final	**0.0005***	**0.0007***	**0.0029***	**1.6968**	**0.0192***
AS100C_AS100P200	*LDA*	0.0006*	0.0007*	0.0028*	0.0066*	0.0165*
	Log. Reg.	0.0007*	0.0007*	0.0033*	0.0069*	0.0206*
	Final	**0.0006***	**0.0007***	**0.0030***	**0.0067***	**0.0190***
CS100Vall_CS100V	*LDA*	0.0005*	0.0006*	0.0033*	0.0287*	0.0153*
	Log. Reg.	0.0033*	0.0009*	0.0168*	0.1002	0.0566
	Final	**0.0017***	**0.0007***	**0.0090***	**0.0281***	**0.0290***
AS100P50all_AS100P50	*LDA*	0.0006*	0.0007*	0.0046*	0.0100*	0.0060*
	Log. Reg.	0.0006*	0.0007*	0.0032*	0.0346*	0.0203*
	Final	**0.0005***	**0.0007***	**0.0039***	**0.0193***	**0.0147***
AS100Call_AS100P200	*LDA*	0.0006*	0.0007*	0.0046*	0.0153*	0.0060*
	Log. Reg.	0.0007*	0.0007*	0.0033*	0.0069*	0.0206*
	Final	**0.0005***	**0.0007***	**0.0039***	**0.0120***	**0.0149***

Conclusion

Parsimonious scores:

- Methods which build a succession of scores from which the user can choose according to its objectives.
- In the application: similar or better results than other scores, with less variables.

Online logistic regression:

- Online standardization of the data helps to avoid numerical explosion.
- Interest of averaged processes with piecewise constant step-size and online standardized data.

Online ensemble score:

- Online ensemble scores converge empirically to the batch score (theoretical convergence already proven).

Conclusion
References

Parsimonious ensemble score:

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